Real-Time Satellite Derived Turbulent Heat Fluxes for ICE-POP

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Background

Bulk flux algorithms relate the turbulent fluxes to near-surface meteorology

$$LHF = \rho C_e (Q_s(SST) - Q_{air})(Wspd)$$
$$SHF = \rho C_h (SST - T_{air})(Wspd)$$

- Estimating the fluxes over the (ice-free) oceans reduces to i) retrieving each of the near-surface bulk variables and ii) application of a suitable bulk-flux algorithm (e.g. COARE 3.5).

Passive Microwave Sensors & Algorithms

- Each of the above parameters have been retrieved using passive microwave observations
- 10-m Qair and Tair (i.e. at a specific level) show only moderate direct sensitivity (unlike SST and surface wind speed). Information on these surface-layer parameters is thus more indirect.

Sensor	Platform(s)	Period of Coverage	Intercalibration Effort	Algorithm Development
SSM/I	DMSP F08-F15	1987 – present	NOAA SSM/I FCDR	Liu (1986) Schulz (1993) Chou et al. (1995) Schluessel et al. (1995) Konda et al. (1996) Jones et al. (1999) Krasnopolsky et al. (2000). Bentamy et al. (2003) Jackson et al. (2006) Roberts et al. (2010)
SSMIS	DMSP F16-F18	2003 – present	NOAA SSMIS FCDR	
TMI	NASA TRMM	1998 – present	GPM Xcal	Kubota and Hihara (2008) Zong et al. (2007) Roberts et al. (2012)
AMSR-E	NASA AQUA	2002 – 2011	GPM Xcal	
WindSat	NRL Coriolis	2003 – present	GPM Xcal	
GMI	NASA GPM	2014 – present	GPM Xcal	

Regression Approaches

Empirical

- Obtain a paired training dataset of observed response variable and independent parameters (e.g. brightness temperatures) and attempt to model the relationship.

(SST, U10, PW, CLW, P, Qa , Ta,) = F(TB_{10V}, TB_{10H} ,TB_{19V}, TB_{19H}, TB_{22V}, TB_{37V}, TB_{37H}, TB_{85V}, TB_{85H})

From statistical decision theory, finding a "best" model for predicting a response variable—under squared error loss— results in the optimal solution (Hastie et al. 2009):

$\boldsymbol{f(x) = E(Y|X = x)}$***, i.e. the conditional expectation***

- Direct empirical methods make assumptions on the form of these conditional relationships and then estimate parameters of the model using a large paired dataset.
- All current satellite-based latent heat flux products use some form of empirical regression for specific humidity and/or wind speed, air temperature, sea surface temperature.
  - GSSTF 3.0, HOAPS 3.2, IFREMER 4.0, JOFURO 2.0, OAFlux 3.0, SEAFLUX-CDR 2.0

Real-time turbulent fluxes

- The Integrated Multi-satellitE Retrievals for GPM (IMERG) includes a real-time data stream product
- While IMERG RT is focused strongly on precipitation estimates, the Level 1C (intercalibrated) brightness temperatures from contributing passive microwave instruments are also included. *Thus, there is an opportunity to apply well-established retrievals to these L1C data to estimate surface bulk variables and turbulent fluxes*

Platform(s)	Sensor	Freq	Freq	Freq	Freq	Freq	Freq	Freq	Freq
F16, F17, F18	SSMIS		19.35 V,H	22.235 V	37.0 V,H	91.665 V,H			
GPM	GMI	10.65 V,H	18.7 V,H	23.8 V	36.5 V,H	89.0 V,H	160.0 V,H	183.31 +/- (3,8)	
GCOM-W1	AMSR-2	10.65 V,H	18.7 V,H	23.8 V,H	36.5 V,H	89.0 V,H			
NPP	ATMS			23.8 QV	31.4 QV	88.2 QV	165.5 QH	183.31 +/- (1,1.8,3,4.5,7)	
Megha-Tropiques	SAPHIR							183.31 +/- (0.2, 1.1, 2.8, 4.2, 6.8, 11)	
NOAA-18, NOAA-19; METOP-A, METOP-B	MHS					89.0 QV	157.0 QV	183.31 +/- (1,3)	190.3 QV

Total Satellites: 11

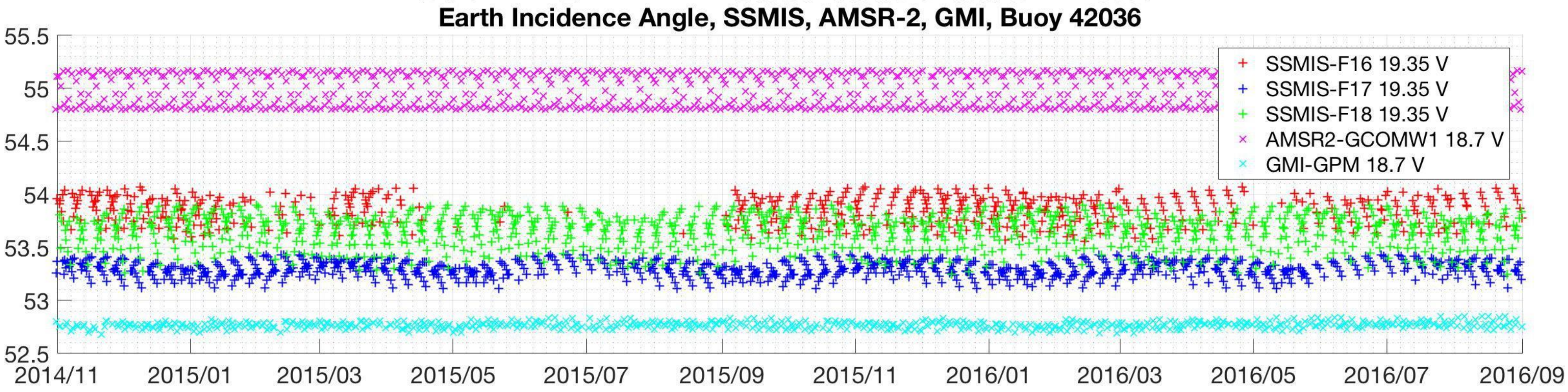
SST

Precipitation, Cloud Liquid Water, Wind Speed, Water Vapor

Water Vapor, Clouds

Intercalibration & Collocation

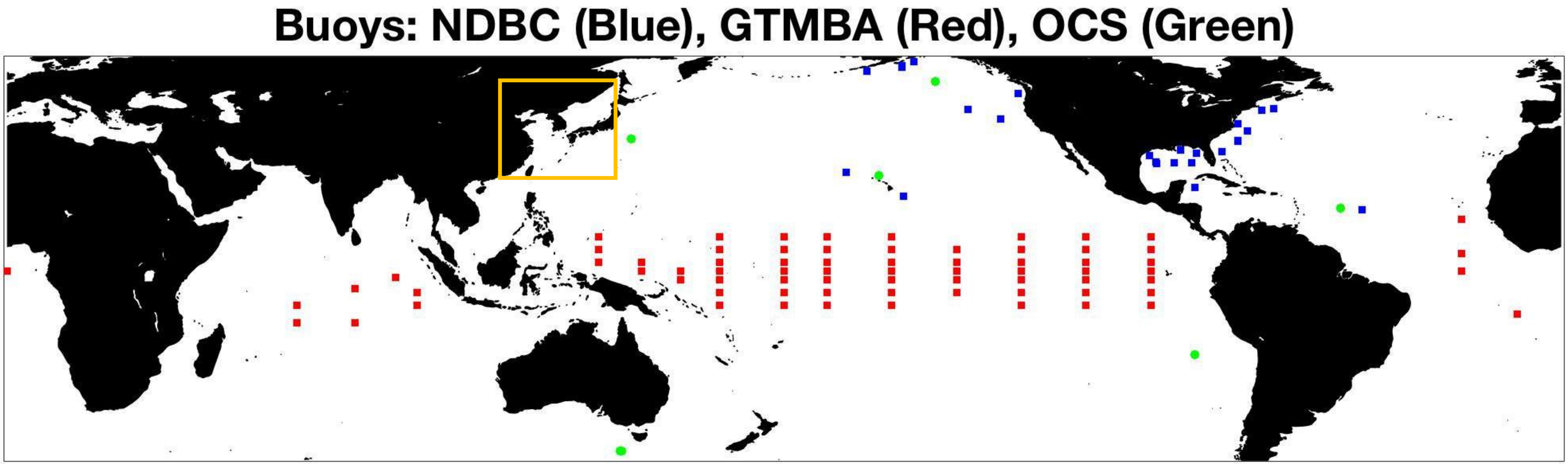
- Even after intercalibration, differences in sensors central frequency and incidence angle can result in systematic differences. Thus, regressions are developed for each unique platform-sensor combination.



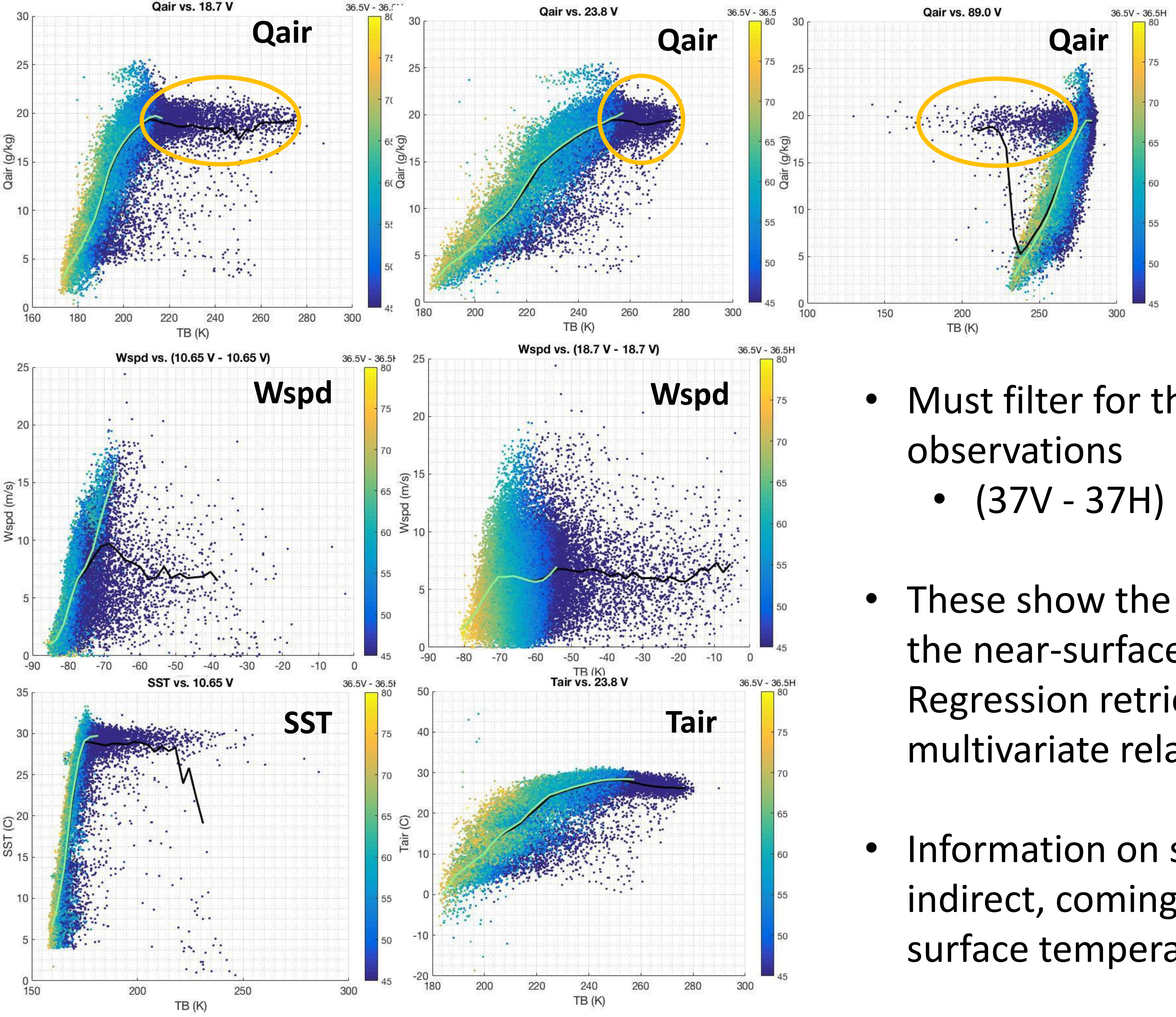
<u>Collocation Dataset</u>

- Hi-resolution (hourly or better) surface observations were obtained from several oceanographic moored buoy data archives:
    - US National Data Buoy Center (NDBC)
    - NOAA PMEL Global Tropical Moored Buoy Array (GTMBA)
    - OceanSITES - NTAS, WHOTS, STRATUS { Ocean Reference Stations (Woods Hole Oceanographic Institution)}
    - PMEL Ocean Climate Stations - ARC, KEO, Papa
- Observations were filtered based on quality control metrics; only times in which all surface bulk variables required for turbulent flux computation were kept.
- Each platform-sensor was collocated to surface observations in the closest hourly interval with the requirement that the observation is within 25km of the surface observation. Only the single, closest observation per ascending/descending orbit was kept.

Spatial Distribution - Surface Buoys



- ~100 moored buoys available over the 2014-2016 period of L1C data coverage
- Spatial coverage strongly favors tropical latitudes; higher latitude coverage originates primarily from the NDBC buoys
- More data for evaluation over ICE-POP region needed: ***KMA and/or JMA buoys?***



GMI Conditional Relationships: {Qair, Tair, Wspd, SST} vs. TB

- Must filter for thick clouds/rain impacts on satellite observations
  - (37V - 37H) < 45K ; Mask retrievals
- These show the *univariate* relationships between the near-surface values individual sensor channels. Regression retrievals will depend on the multivariate relationships.
- Information on surface air temperature is highly indirect, coming from it covariability with both sea surface temperature and humidity

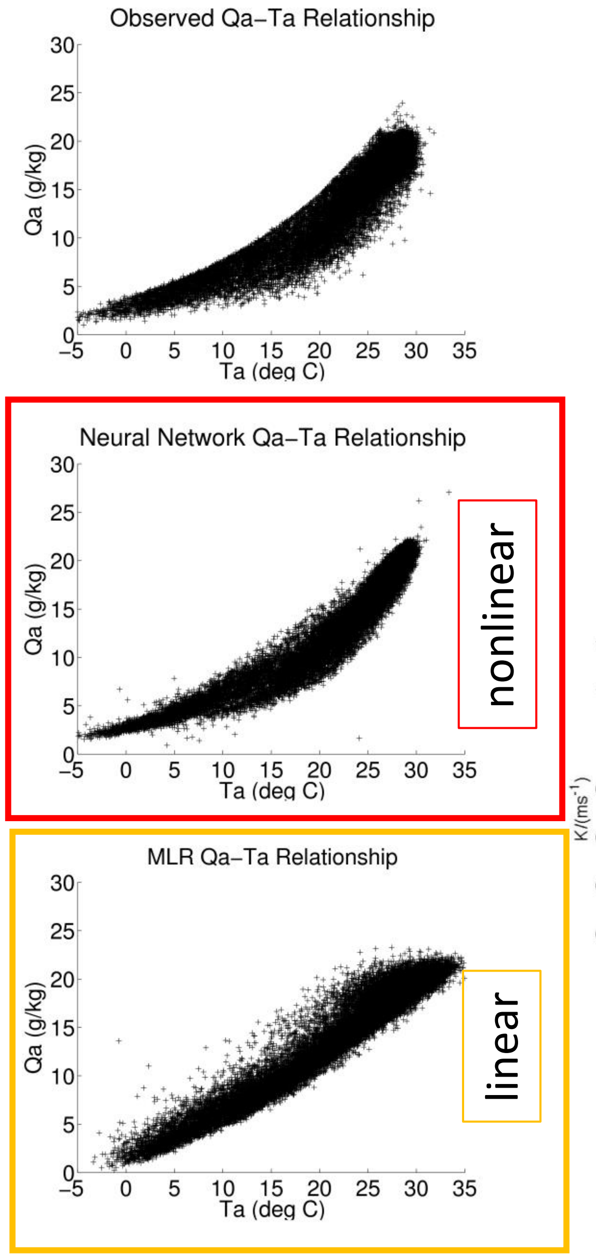
Regression - (Nonlinear) Neural Network

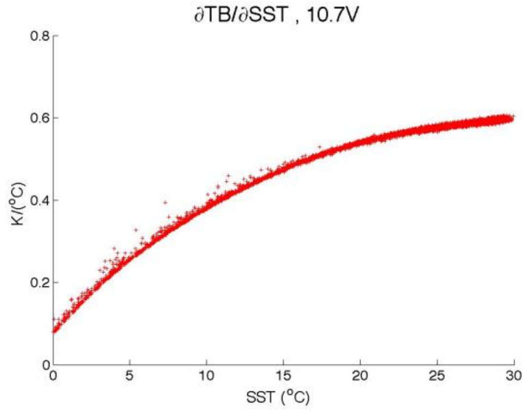
<u>Multivariate Relationships</u>

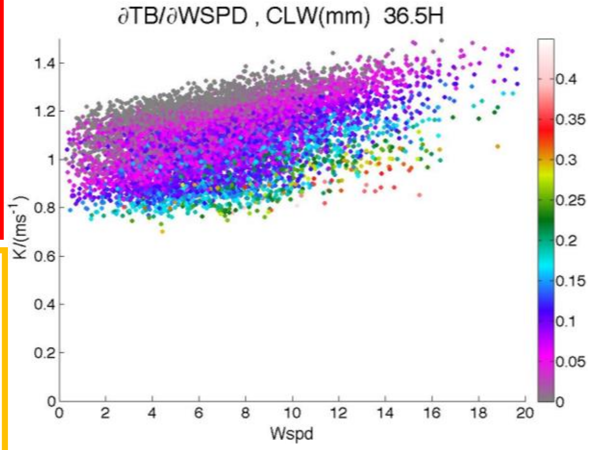
- Qair/Tair: Clausius-Clapeyron relationship imparts a strong connection
- SST/Tair: The sea surface temperature and air temperature are typically with ~1-2 C of one one another
- PW/Qair: Total columnar water vapor (precipitable water) and surface air humidity are correlated).

<u>Nonlinearity</u>

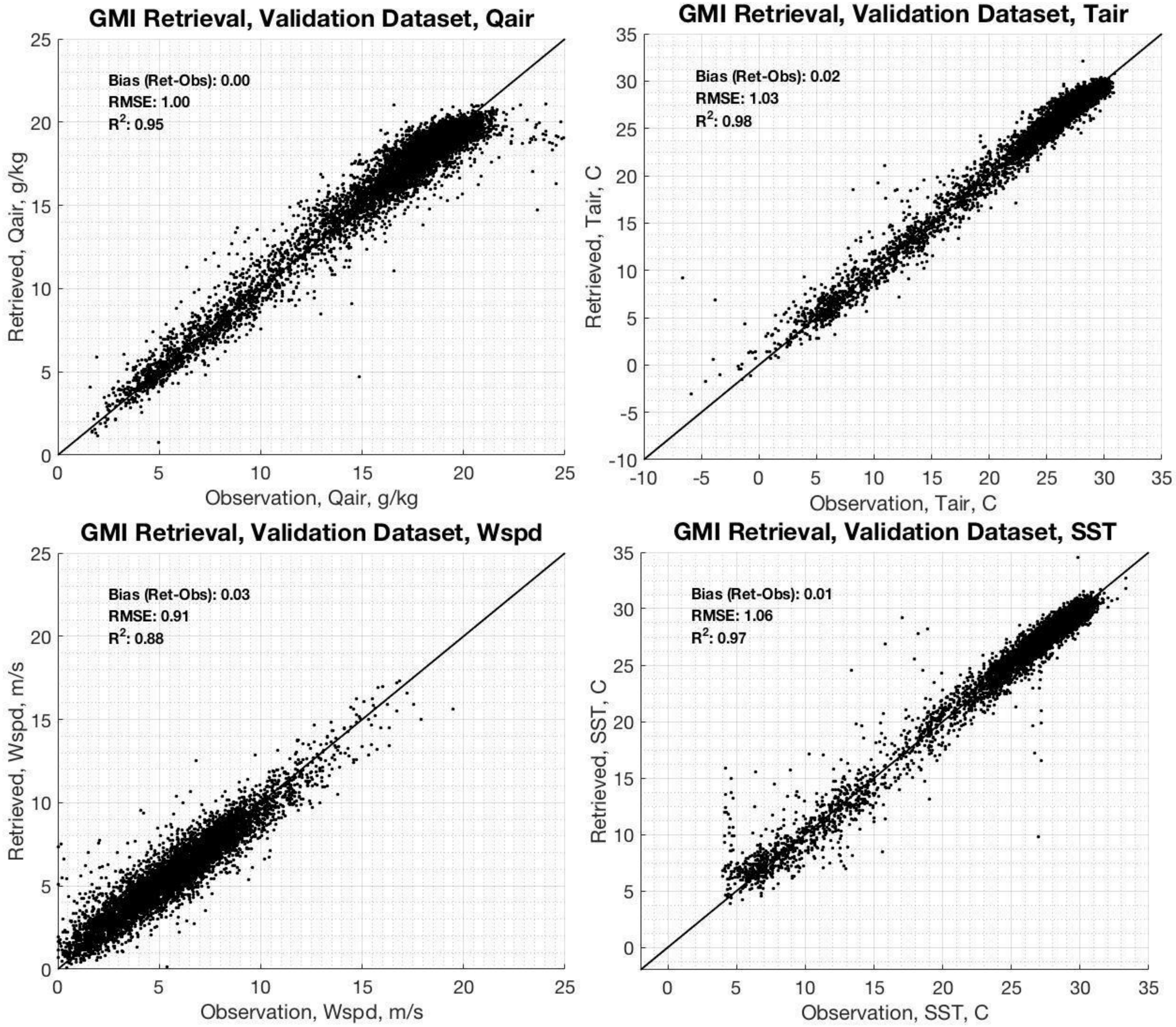
- Dependence on atmospheric stateDependence on surface conditions
- Inherent relationships between moisture and temperature.
- *Thus, we expect a nonlinear regression to be more appropriate for our regression model*







Results - Neural Network Retrieval



Model

[Qair, Tair, Wspd, SST] =

F_{NNET}(10V,10H,18V,18H,23V,36V,36H,89V,89H)

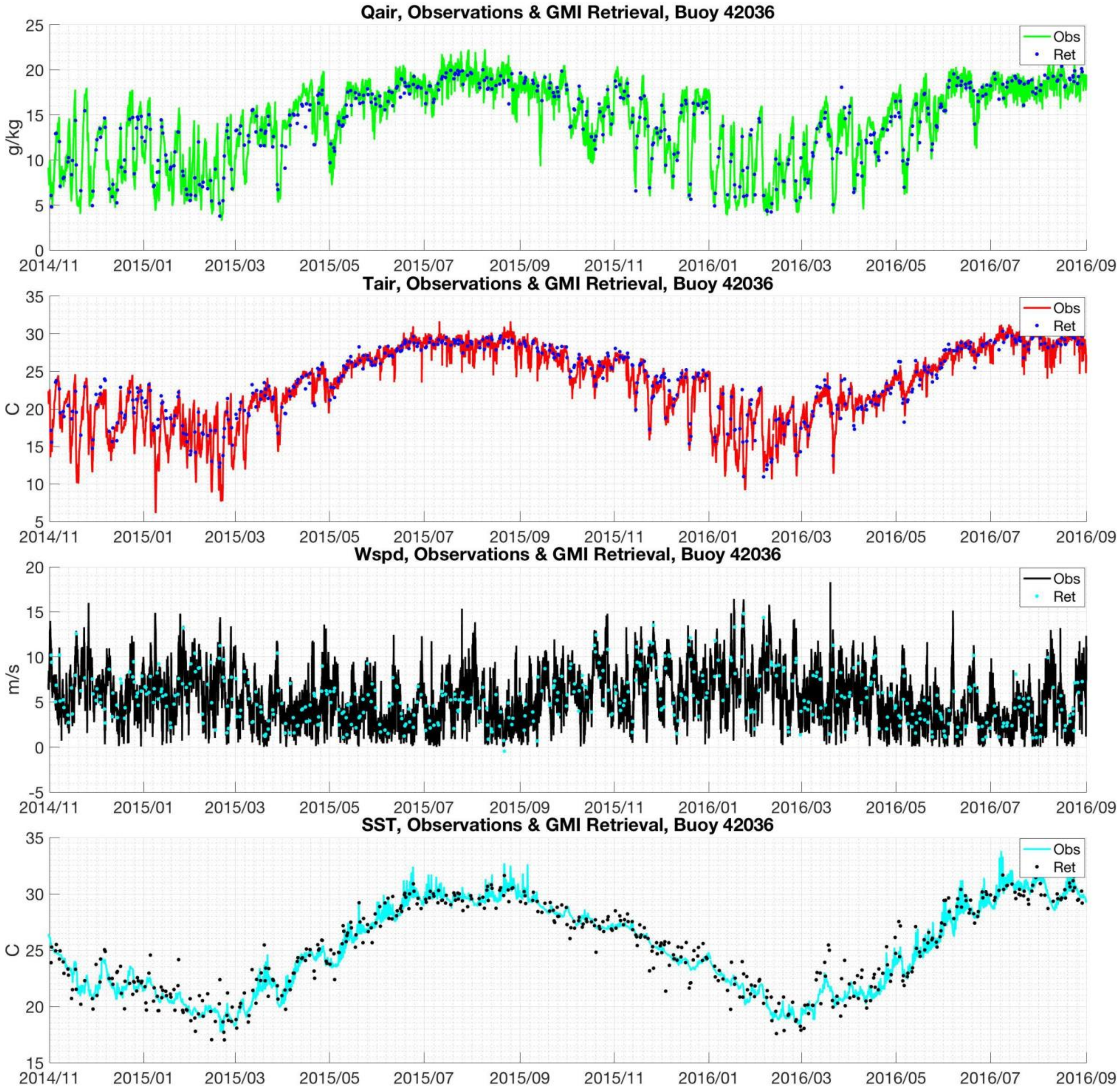
{37V-37H < 45K Masked}

Training

- Masking: Removes ~10% of values
- 33827 Collocated pairs
  - Training: 27062 (80%; 60% + 20%)
  - Testing: 6765 (20%)
- Results relative insensitive to training algorithm and observational splitting into Training/Cross-Validation/Testing sets

Performance

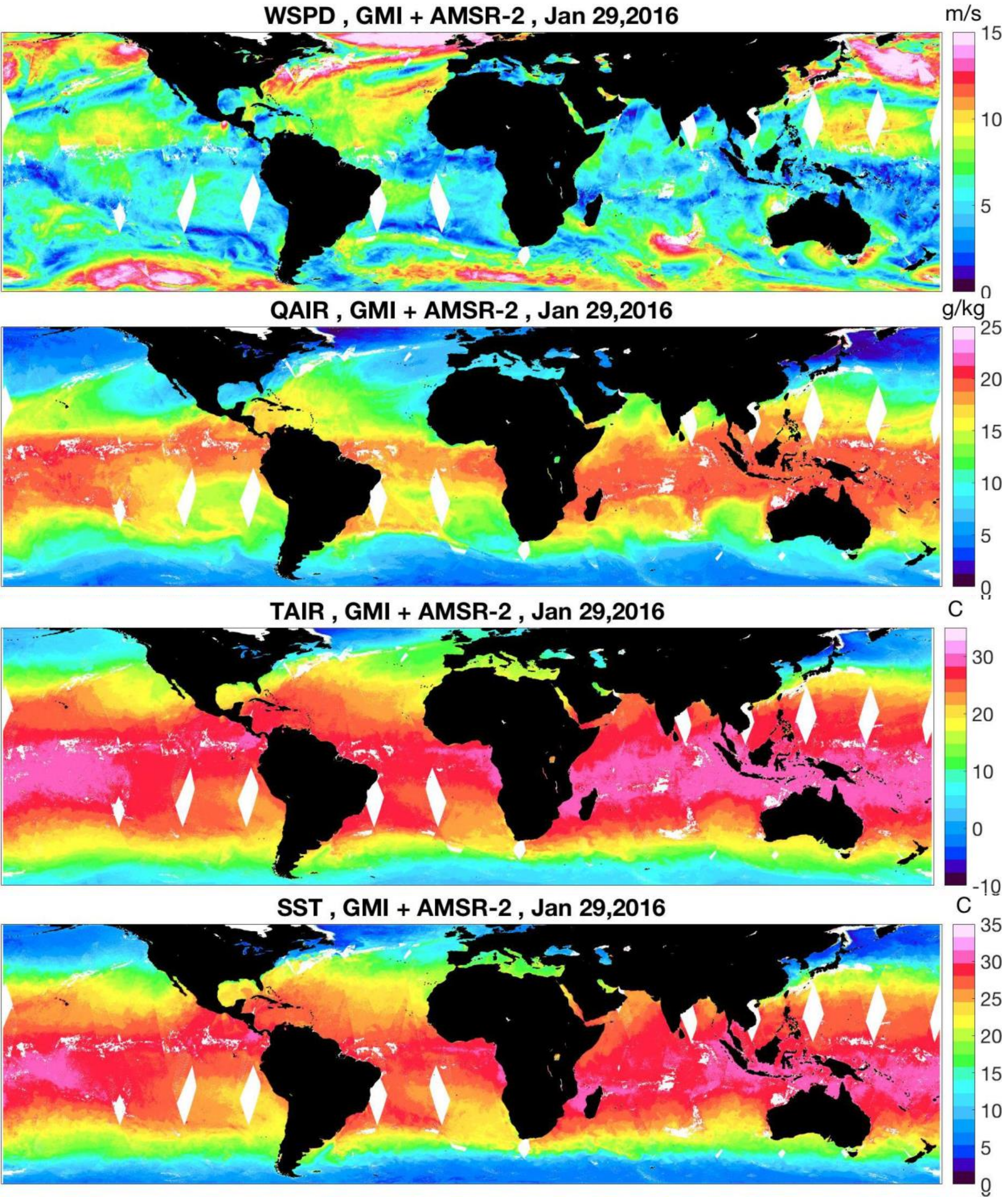
- R^2 ~0.9 or better for all parameters
- Small bias and RMSE ~1.0 (g/kg, C, m/s) for all parameters
- Some outliers present; may require additional flagging



Example - Buoy Time Series

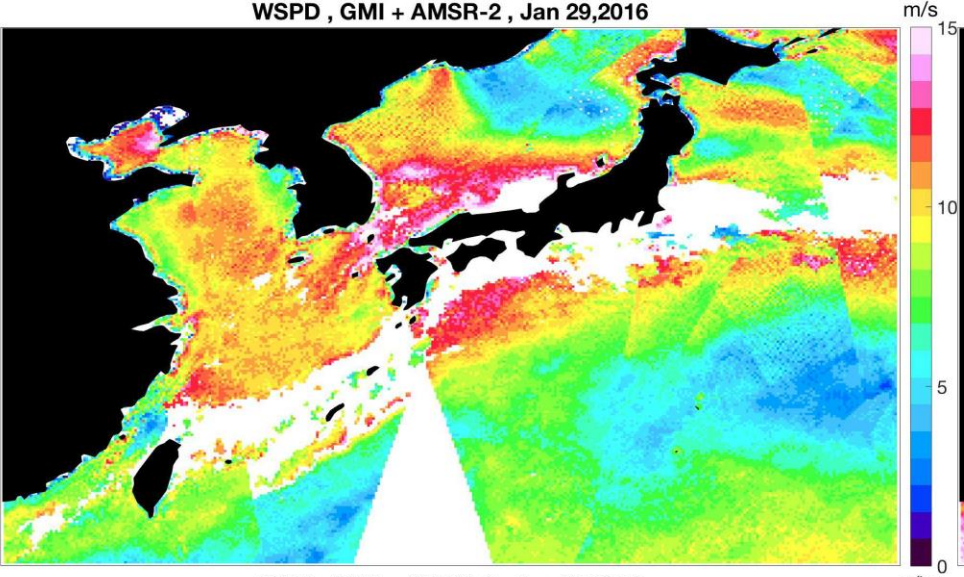
- Buoy 42036 - Gulf Of Mexico
  - Cold air outbreaks common in the winter
- Generally, the GMI retrievals capture the seasonal and high-frequency variability as observed by the buoys.
- *Need additional buoys for independent evaluation, especially relevant for ICE-POP domain*

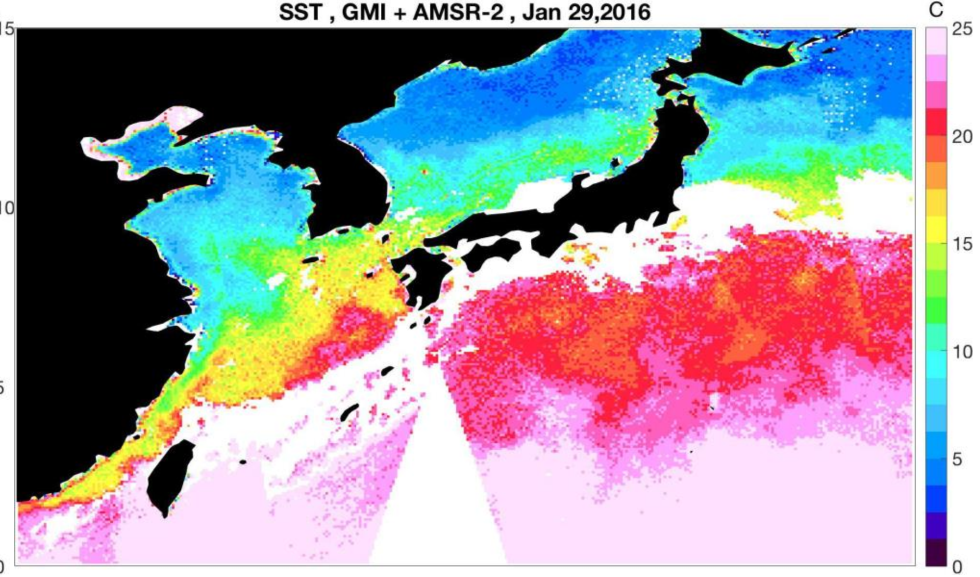
Example - Global Map

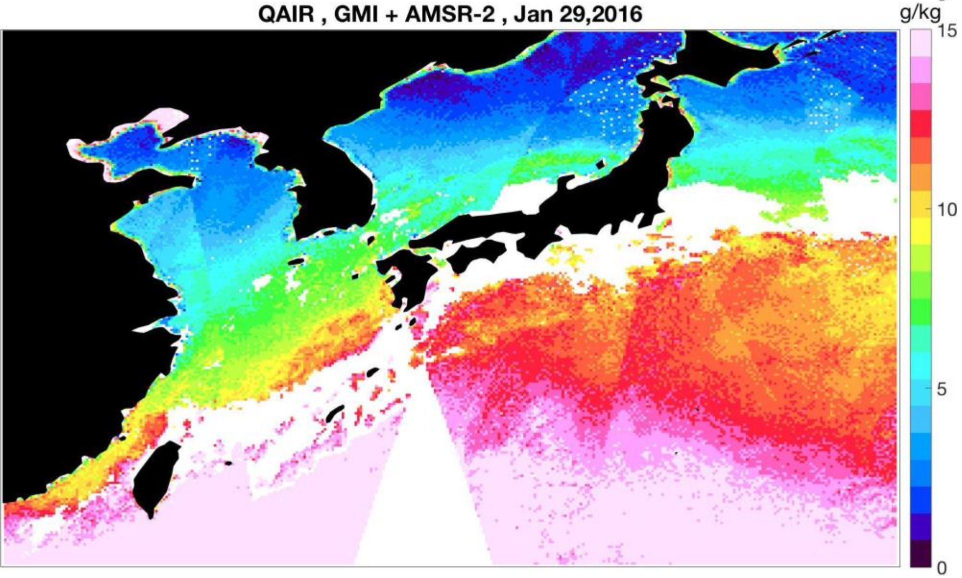


- Excellent daily coverage even with only two sensors
  - Expect up to 5 microwave imagers in total

- Retrievals between sensors, at first sight, appear to be very similar
  - Quantification of differences remain to be performed







Example - ICE-POP Region

- Gridded to 0.1x0.1 degree resolution. Captures small scale and synoptic features; Masking impacts primarily along the leading edge of the cold front.
- Coastal land intrusion present; Need to implement both land and sea-ice masks
- Work remains to “stitch” together multiple sensors

Summary

- Real-time turbulent latent and sensible heat fluxes can be generated using GPM IMERG L1C intercalibrated passive microwave observations to retrieve near-surface bulk variables.
- We have collocated all of the L1C microwave observations from 11 platforms/sensors with a large dataset of surface buoy observation and generated a retrieval algorithm for the microwave imagers

Future Improvements

- Develop retrievals for sounders
- Obtain ICE-POP regional surface buoy observations for further evaluation and development
- Implement objective analysis/gridding of retrieved bulk variables with uncertainty estimates